



Harnessing ML and NLP for Elevated Customer Experiences

The DataHour

Seth Levine

Lead ML Scientist, Loris

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About Me



- Lead ML Scientist at Loris
- Host of Learning from Machine Learning Podcast
- M.S. Computer Science
- B.A.S. Complex Human Behavior and Evolution



Loris



Agenda

- 
- What is Loris?
 - What ML & NLP Challenges do we face?
 - Topic Modeling using BERTopic
 - Text Classification with SetFit
 - Evaluating ML Models
 - Demo
 - Takeaways
 - Q&A



What is Loris?

Company Highlights

Clients Include:

FINTECH

flex. bill zip

TECH

fiverr slice

TELECOM

mintmobile ultra mobile

ECOMM

thesis barkbox

BPOs

horatio redial.

Investors Include:

FLOODGATE

vertex
VENTURES



homebrew



Jeff Weiner
(LinkedIn)

bowcapital servicenow

NYC,
TLV

Offices

2018

Founding

>200M
interactions analyzed

6 continents

Global

Loris



QA (1%)

The Problem

Every company's greatest asset
is its most underutilized

Billions of customer interactions contain a
goldmine of untouched insights

Surveys (9%)

The Solution

We use AI to transform every customer interaction into an opportunity for insights, optimization and growth

Loris' Approach

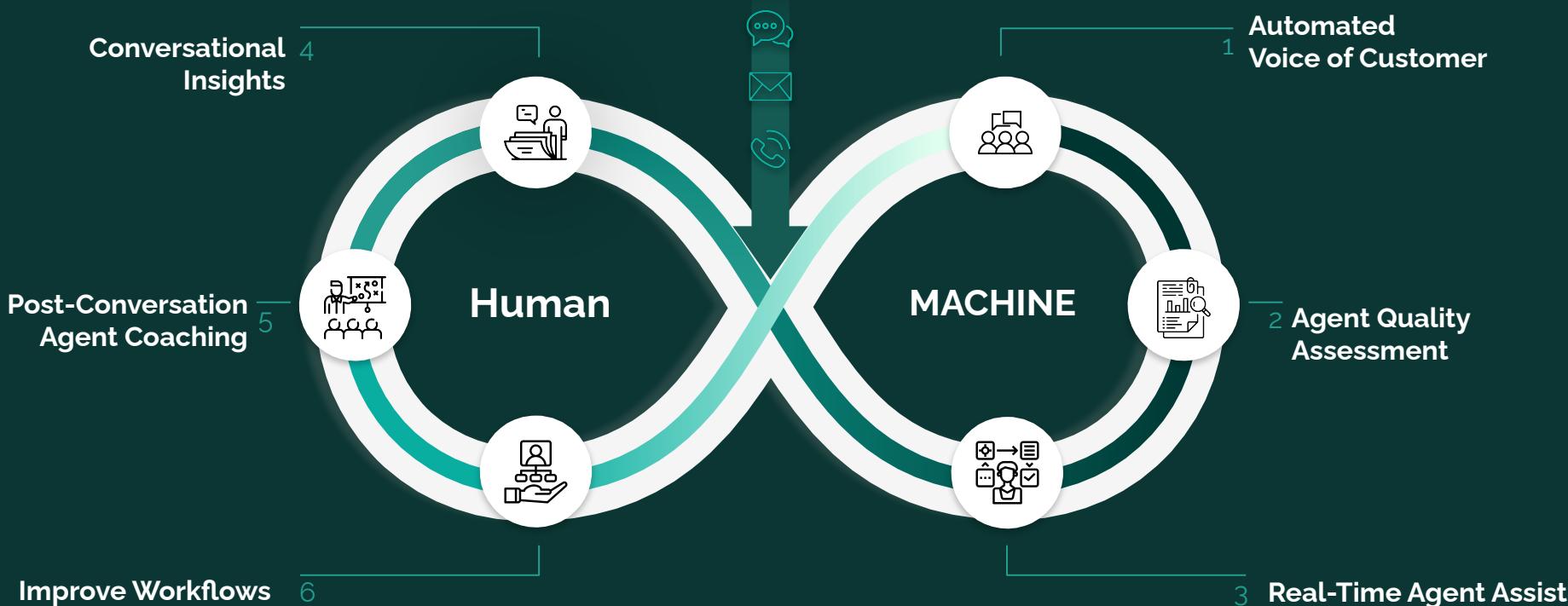
Insights

- The challenge is modeling a domain to solve its specific problems
- Foundation models are becoming a commodity (both commercial and OS)
- Understanding the domain and gathering the right data is a differentiator

Approach

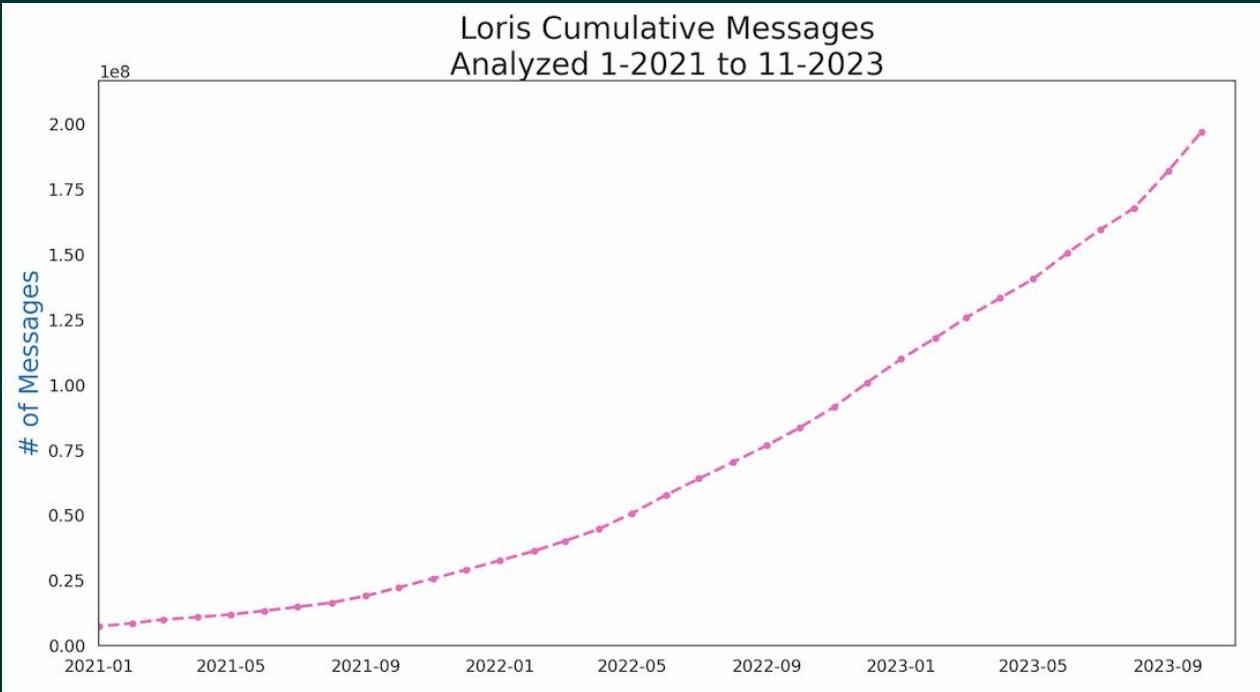
- Model the domain of customer support conversations (conversation phases, dialog acts, etc.)
- Use proprietary data to optimize models for customer support (e.g., Customer Sentiment, Conversation Markers)
- Develop customized Contact Driver models for clients
- Enable a feedback loop on how users interact with our product and predictions

Loris Combines the Best of Humans ∞ MACHINE



Improve customer experience,
operational efficiency, and insight

Our Platform is Scaling Fast



Over 200 million customer care messages analyzed
Analyzing over 5 million messages per month

Omni-Channel



Chats



Emails



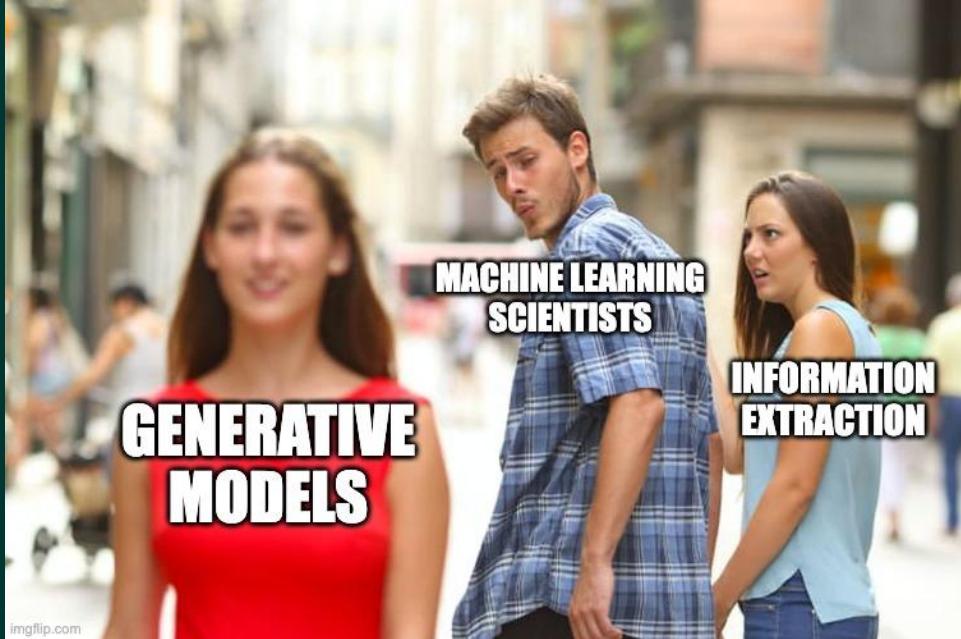
Messaging
Apps

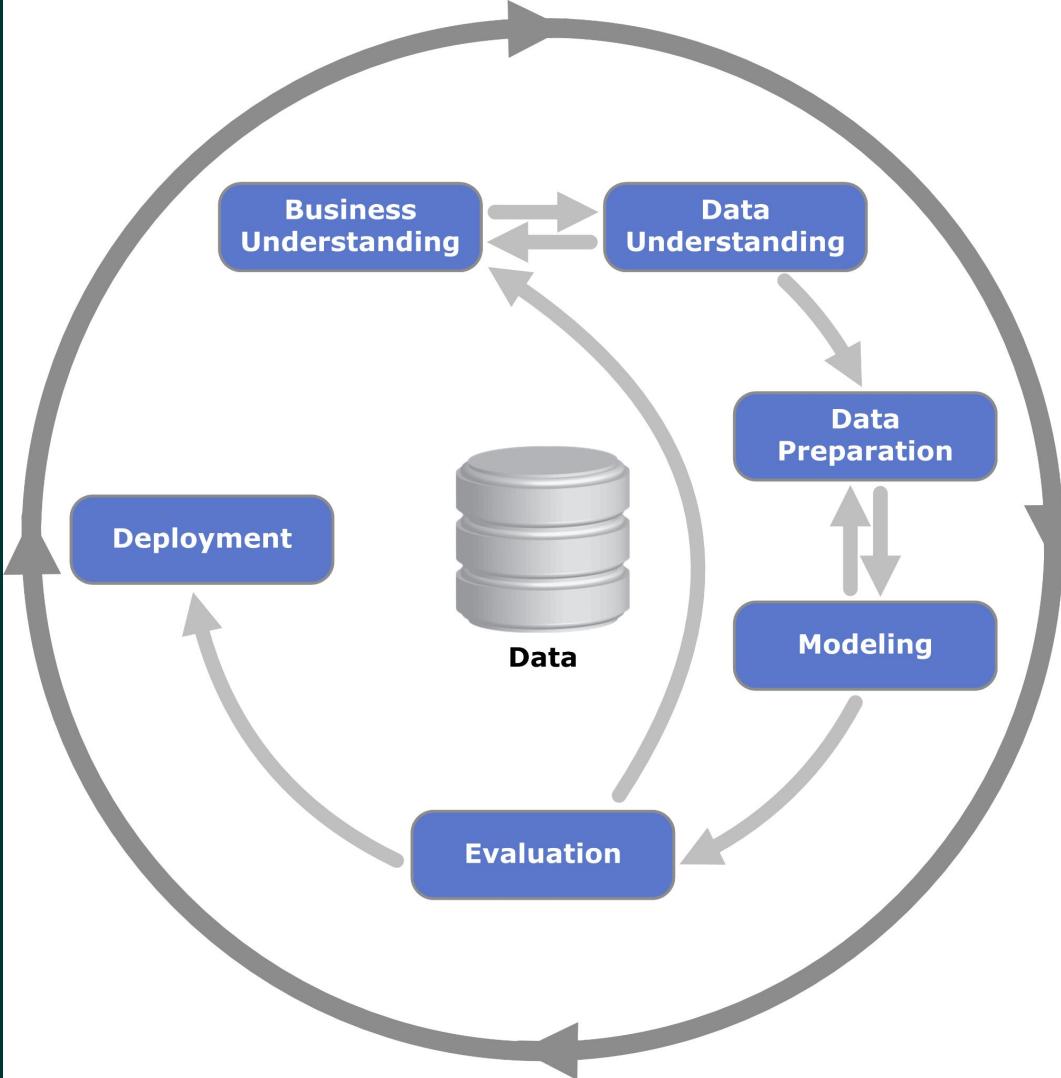


Phone
calls

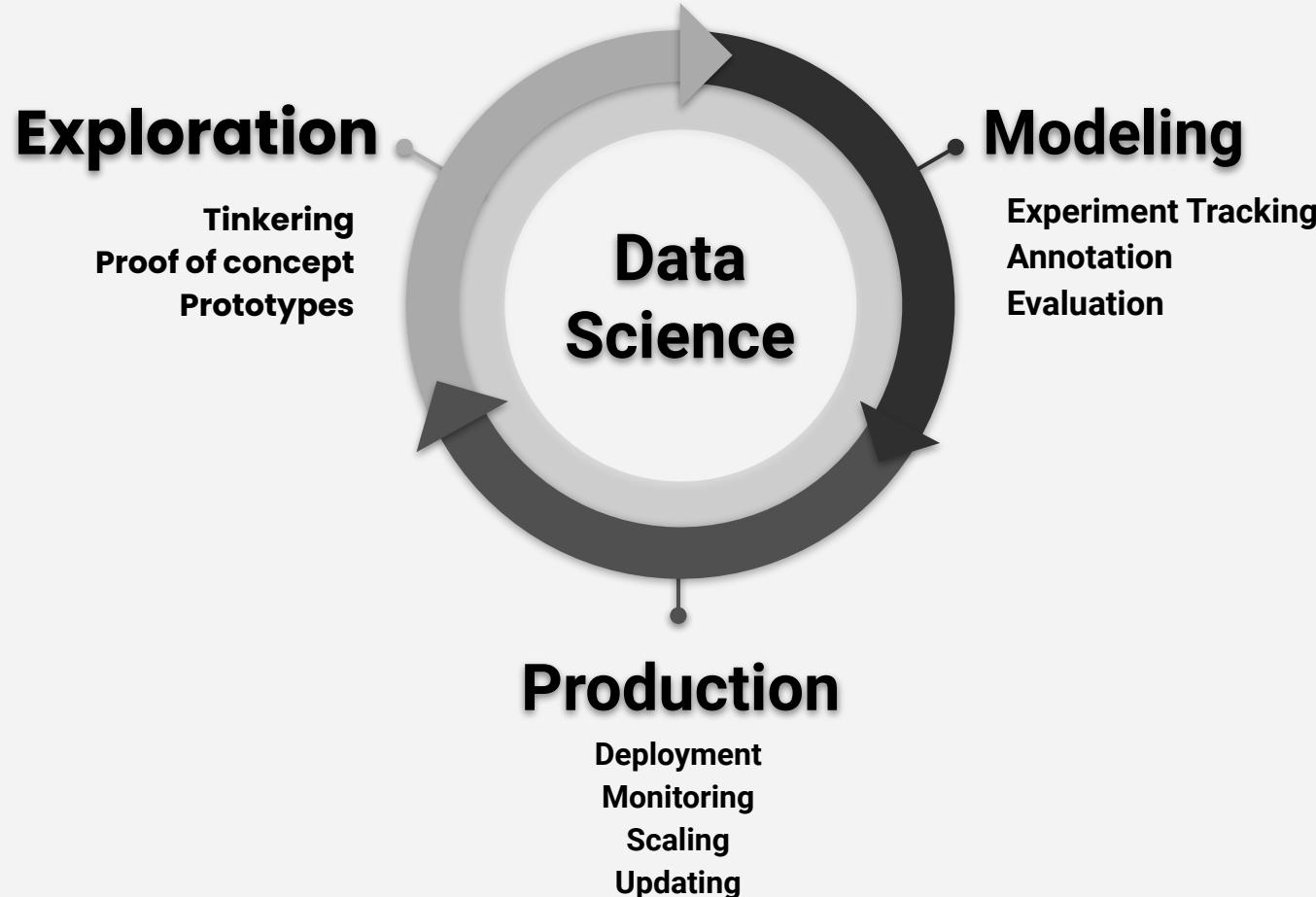
State of Machine Learning

How have ChatGPT-like models changed our approach?





[Cross-industry
standard process for
data mining -
Wikipedia](#)



Machine Learning and NLP at Loris

Main Questions

How is the
customer feeling?



Why did the
customer contact
the company?



How did the
conversation go?

Conversation Modeling and Intelligence

Loris Generalized Models

Message-Level

- Sentiment Model
- Sentiment Target
- Conversation Markers
- Profanity
- Polite Refusal
- Question Detection
- ...

Conversation-Level

- Conversation Quality (CQ)
- Summarizer
- Resolution
- Agent Actions

Loris Custom Client Models

- Client-specific text classification models that each client can use to understand their customers' reason for contact (or intent)

Underlying Need

What problem are we trying to solve?

- Identify what the conversation is about
- Understand a company's contact drivers

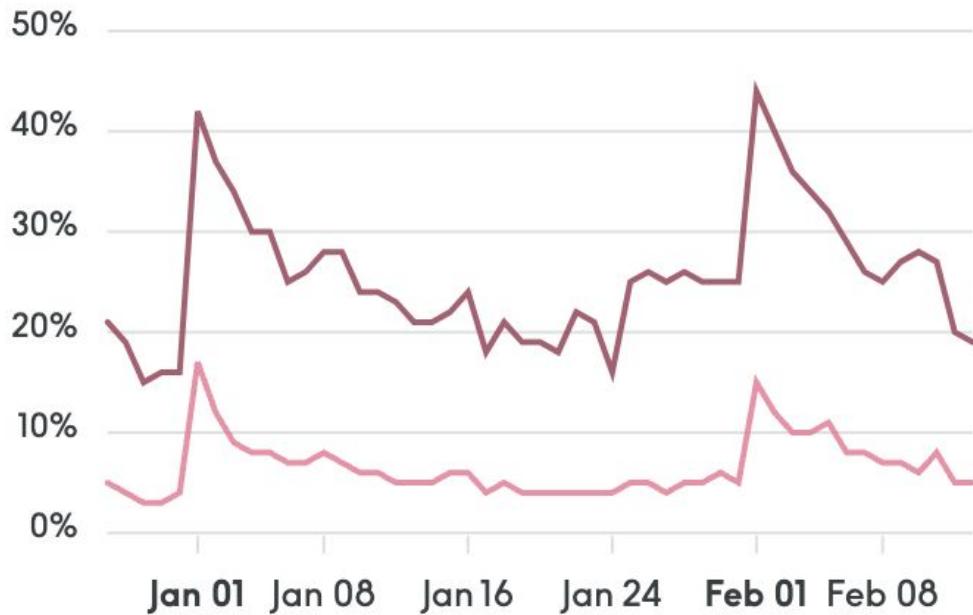
Knowing the contact driver of a conversation allows Loris and our clients to segment conversations into meaningful groups for improvement opportunities

The ability to interpret what a customer is looking for no matter how they word the request

Company can analyze trends, route, create and improve workflows

Intent Frequency Over Time

- Auto Renewal
- Cancel Subscription



Intent Frequency Over Time

- Order Mishap
- Order Status
- Shipping Feedback



Evaluation

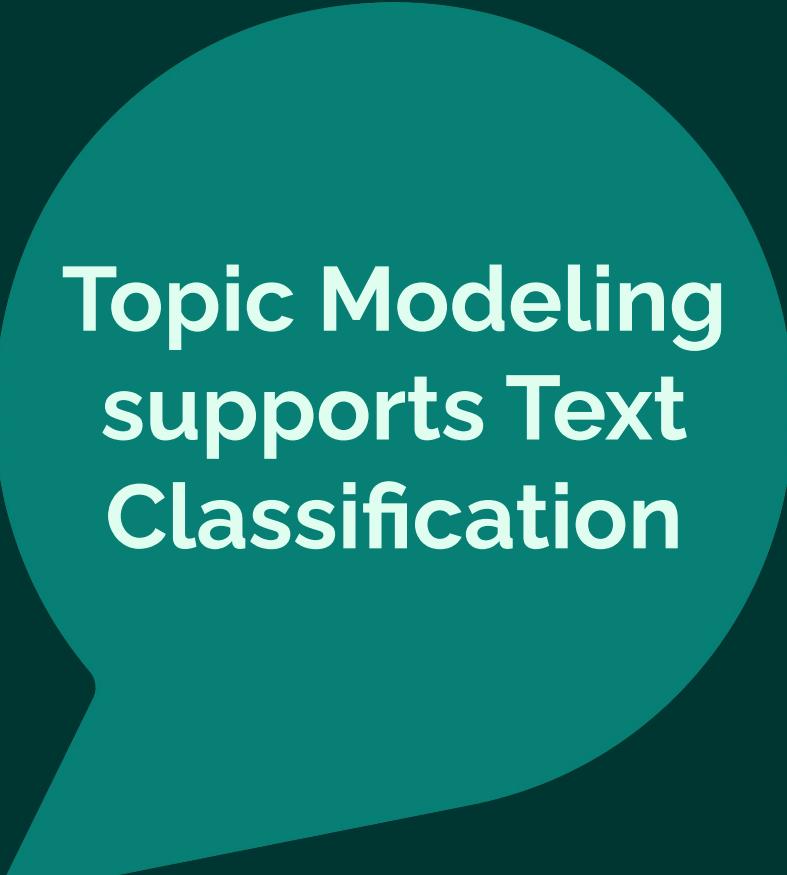
Coverage: % of conversations that are assigned 1 or more intent(s)

Precision: Fraction of detected intents that are correctly predicted

- When an intent is predicted, is it correct?
- Examined on the class-level

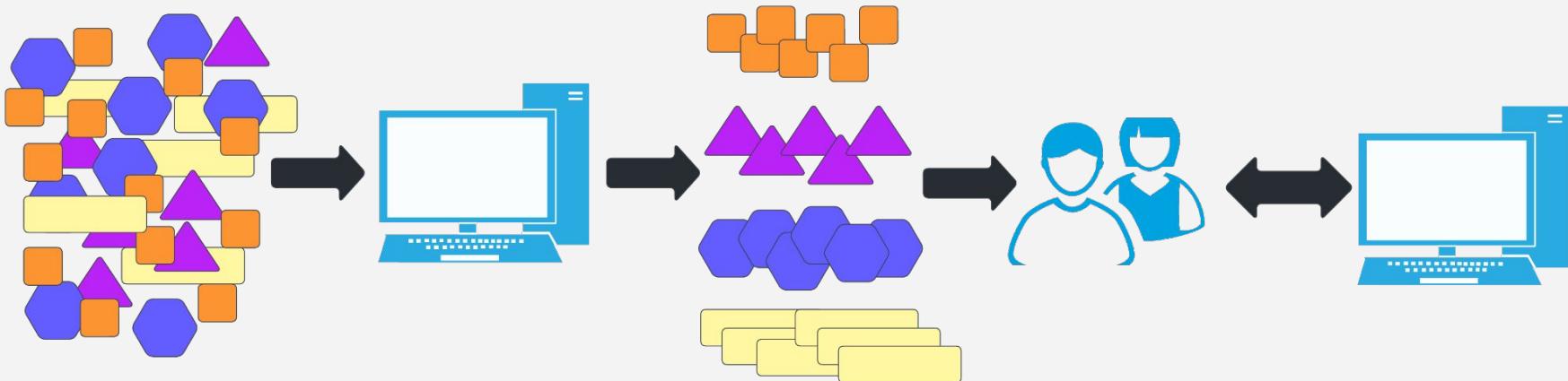
Frequency: In historical data, does the frequency of each contact driver make sense to clients?

- Proxy for recall on the class-level

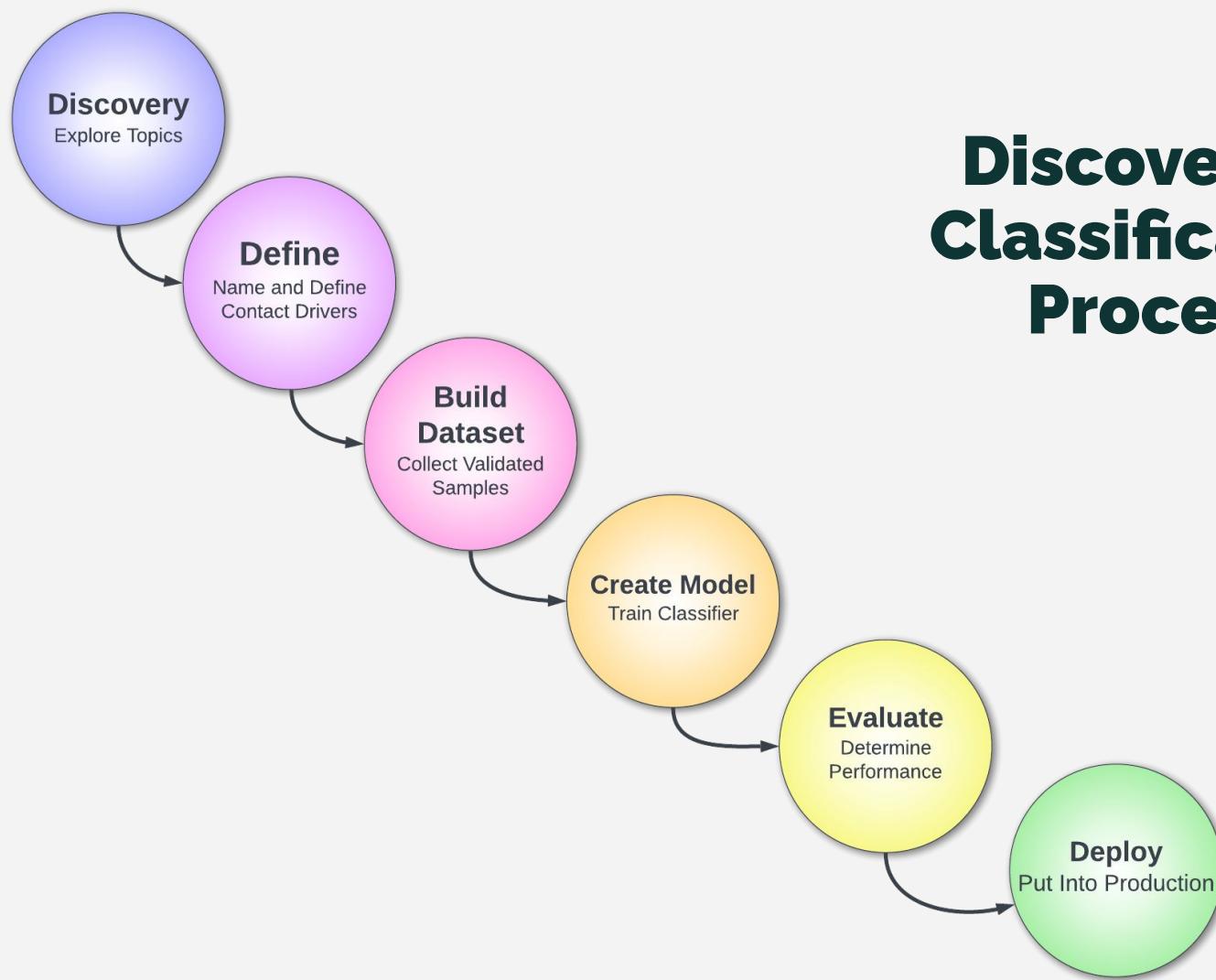


**Topic Modeling
supports Text
Classification**

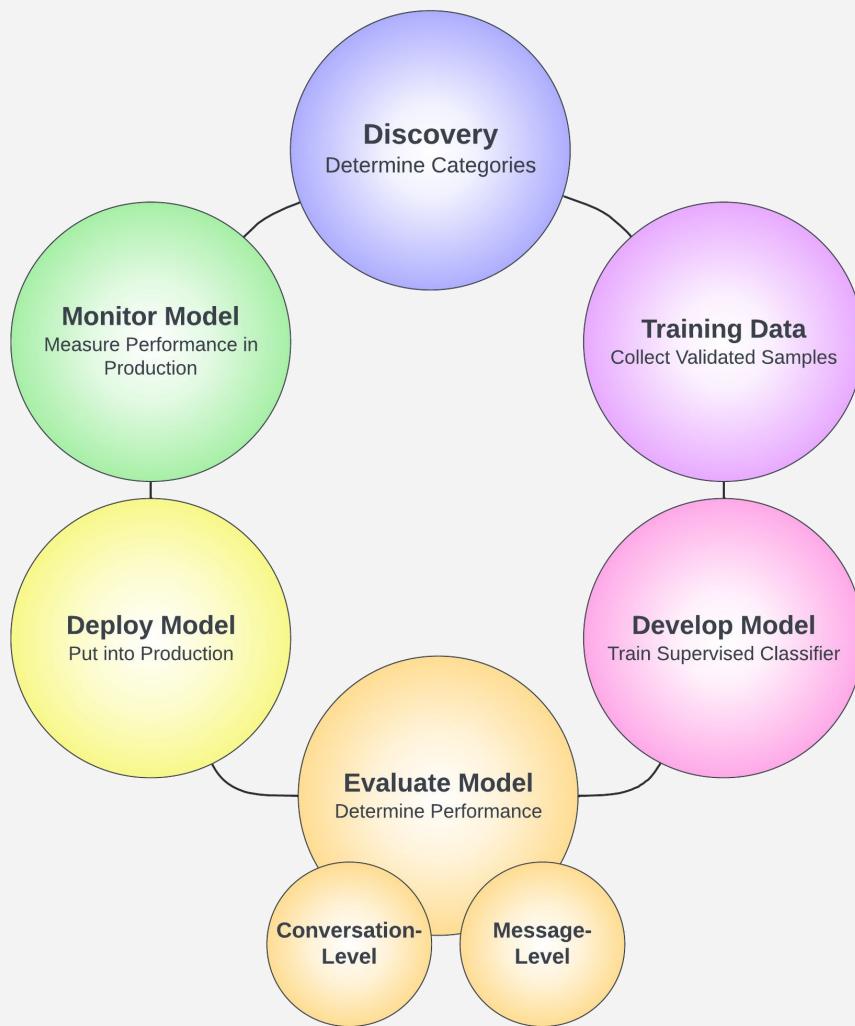
Unsupervised Learning supports Supervised Learning



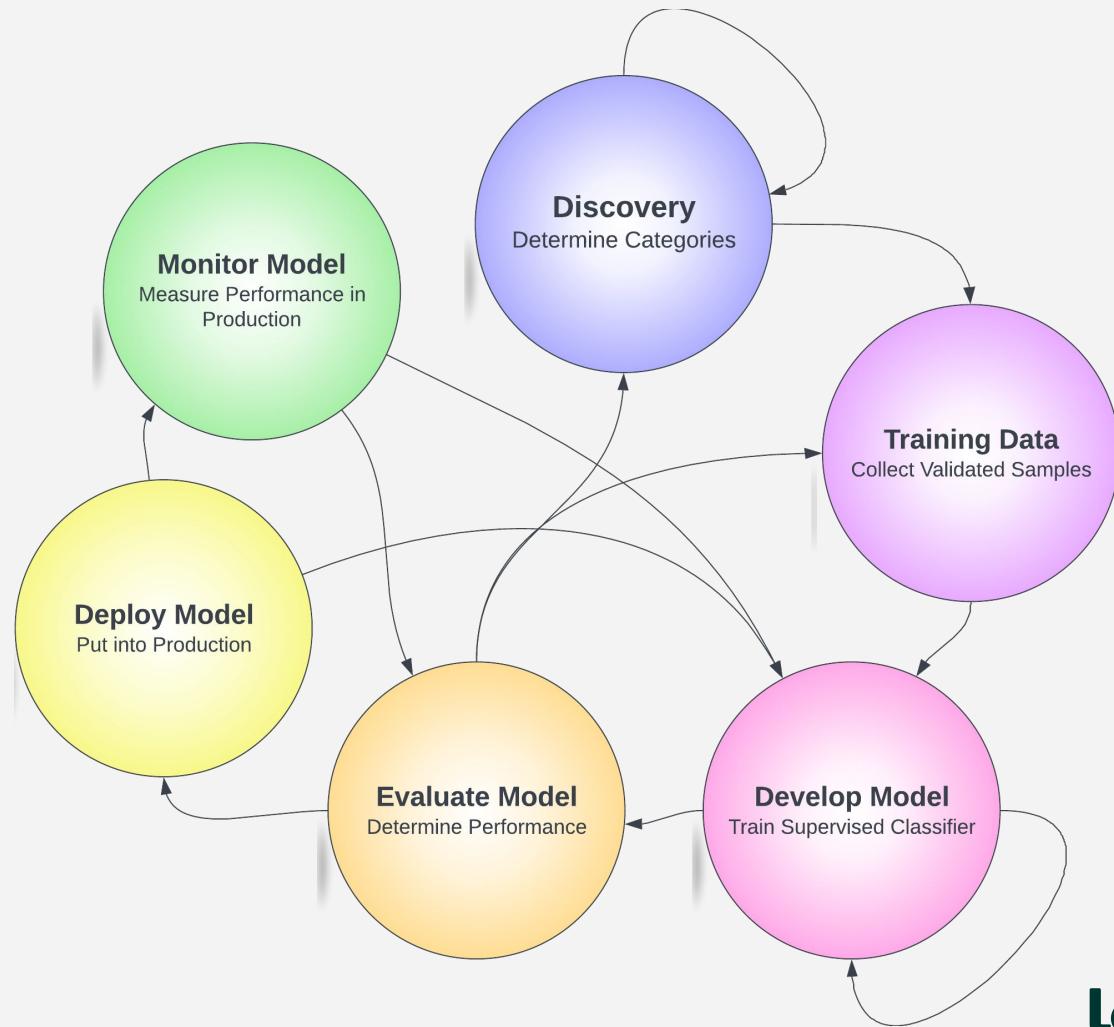
Discovery & Classification Process



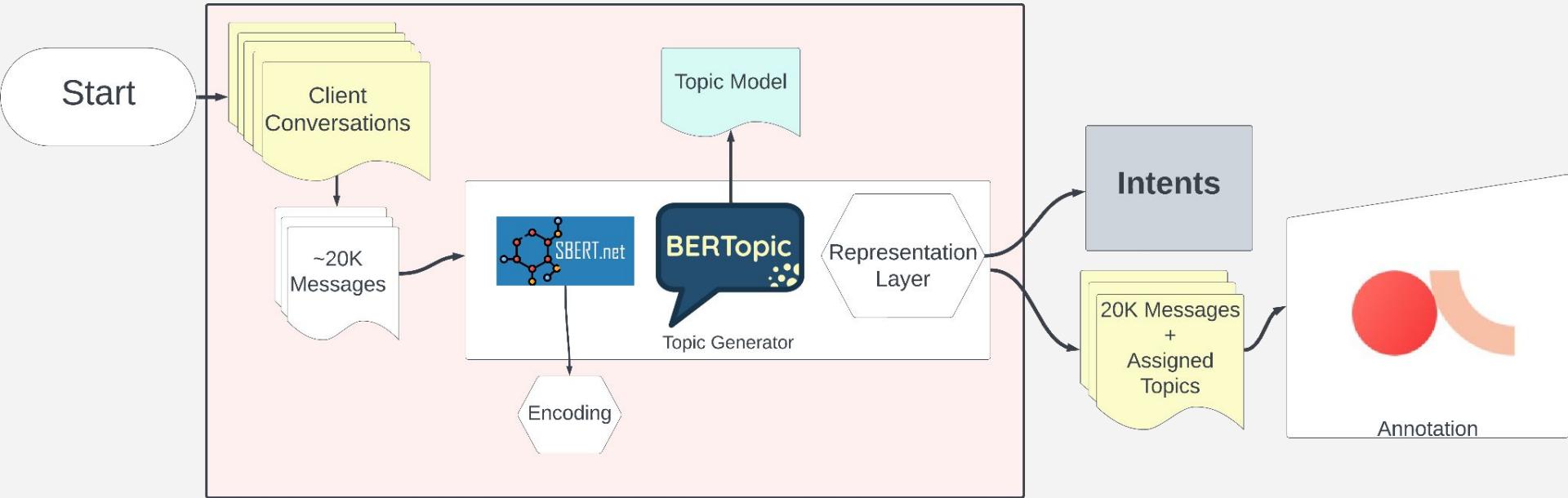
Discovery and Classification Process



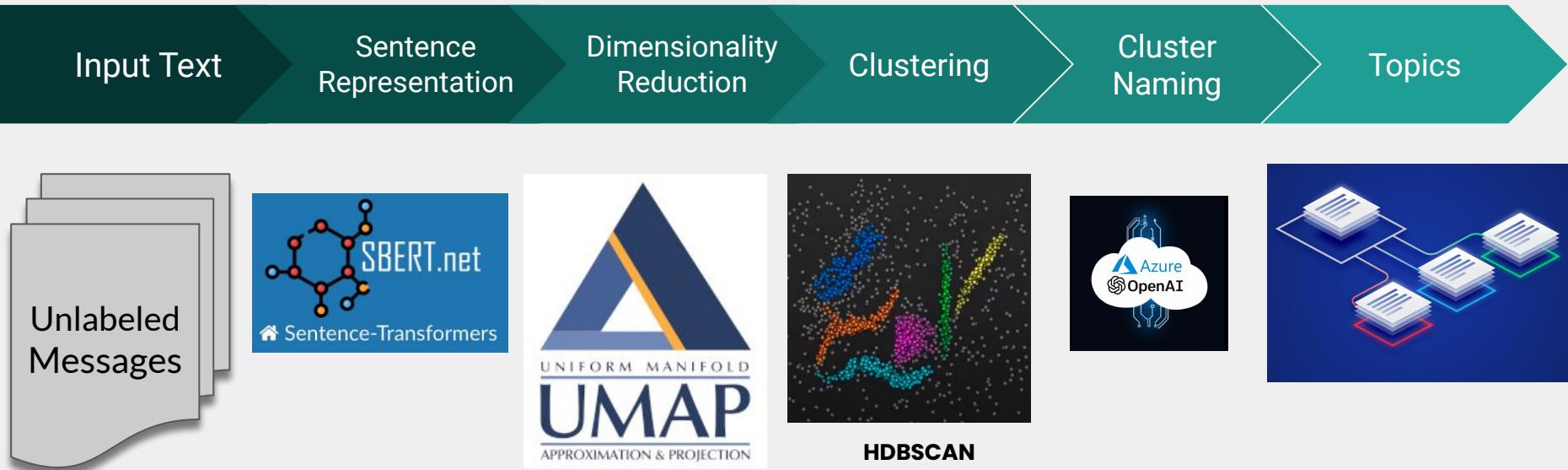
Discovery and Classification Process



Discovery

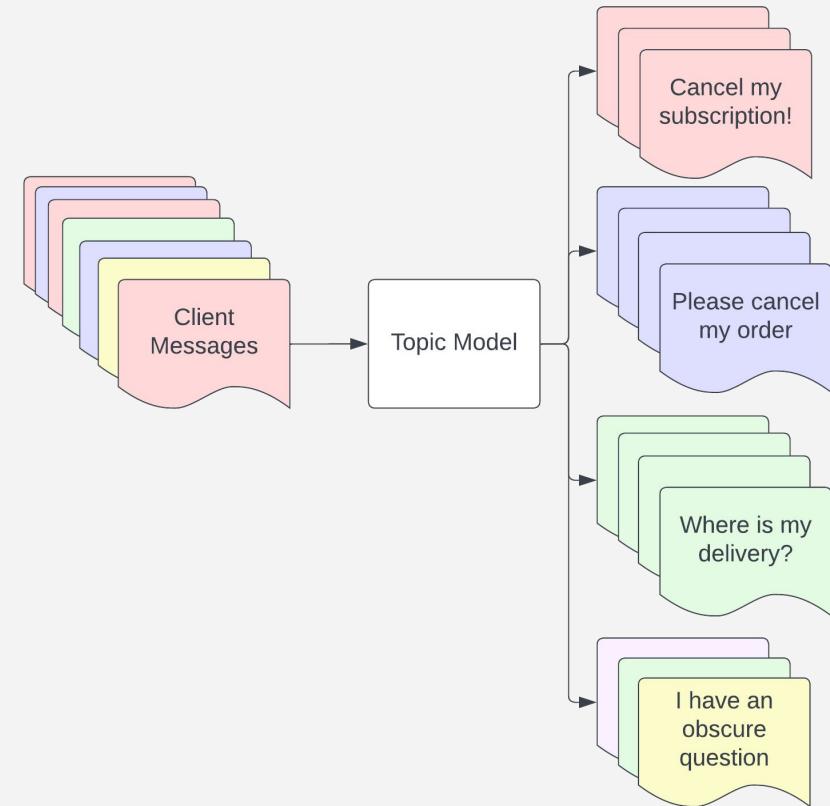


Topic Modeling using BERTopic

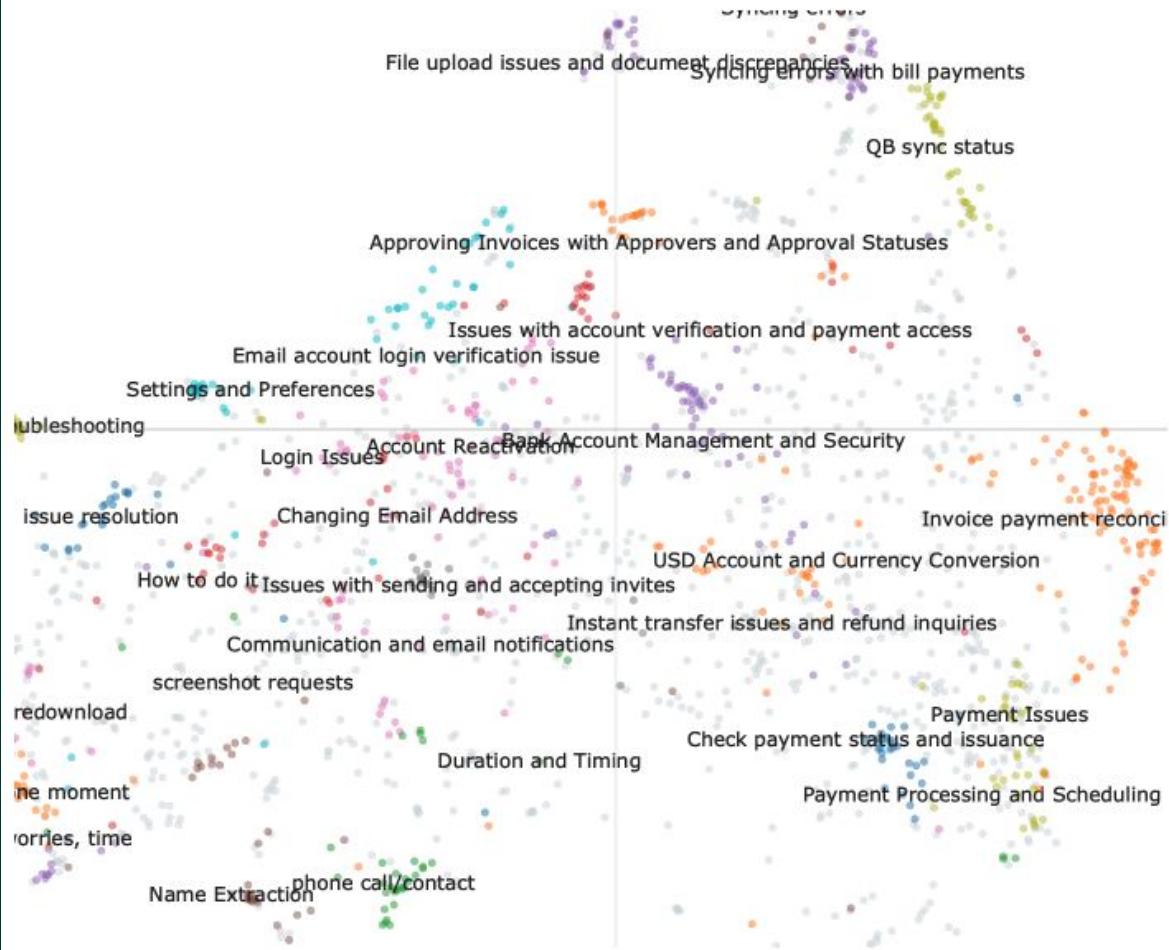


Discovery

- Topic Modeling
- Use unsupervised learning to find structure in data
- Create clusters and groups of messages
- Leverage many techniques
 - Unsupervised learning
 - Seeded topic modeling
 - Multi-aspect representation
- Generate Names for Topics
- Generate Definitions for Topics
- Output representative samples for each topic



Documents and Topics



- Issues with sending and accepting invites
- error troubleshooting
- Settings and Preferences
- issue resolution
- Approving Invoices with Approvers and Approval Statuses
- QuickBooks Online Bill Pay Announcement
- customer service and client contact
- File upload issues and document discrepancies
- Name Extraction
- trying to redownload
- Updating phone number for account verification
- Payment Issues
- still here
- Issues with Deposit Verification and Payment Processing
- USD Account and Currency Conversion
- Chatting Issues
- How to do it
- password reset issues and email inability
- screenshot requests
- Understanding Payment Fees and Charges
- admin and permissions management
- Payment Processing and Scheduling Issues
- Clarification of meaning
- doing good
- Instant transfer issues and refund inquiries
- Duration and Timing
- Changing Email Address
- worries, time
- communication via Slack and sending screenshots
- Login Issues

Discovery Outputs

- Number of classes
- Generated names of classes
- Generated definitions of classes
- Representative samples for each class

Gather Labeled Samples

- Validate samples in Argilla
- Find a small sample for each class
- SetFit only needs a few samples to train
- We need additional samples to validate model
- Use similar to build up dataset quickly

Label Samples Using Argilla

Introduce a query

Predictions Annotations Status Sort NEW Help

Validate 2023-10-17 20:34 Find similar ...

TEXT:
but i cant use thqat account on my computer so I must switch back and forth

Search labels

seller inquiries 0.134% buyer cancellation r... 0.162% member manageme... 0.137%

fraudulent seller 0.163% payment and billing... 0.221% greeting 0.146% invoice inquiries 0.136%

order quality compl... 0.129% order how to 0.083% account inquiries 96.212% +14

Discard

Mode:

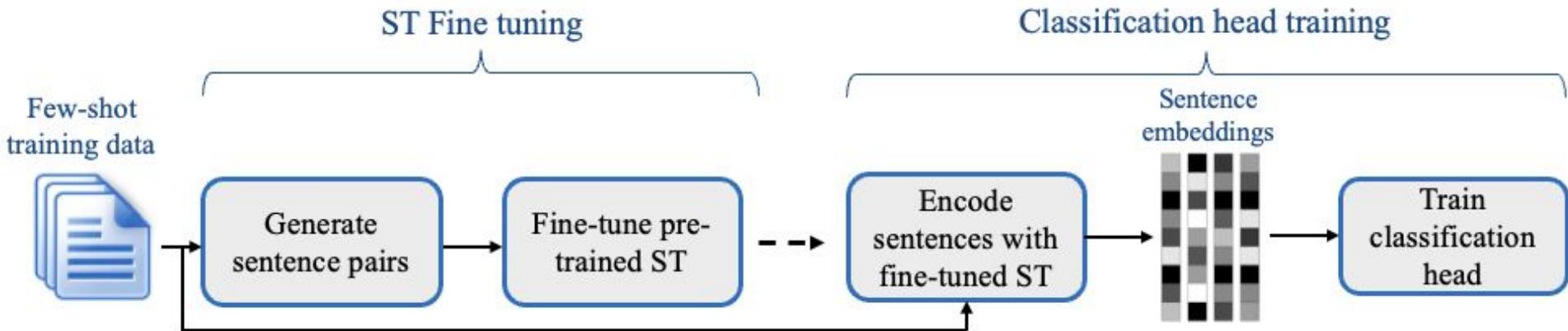
Metrics:

Refresh:

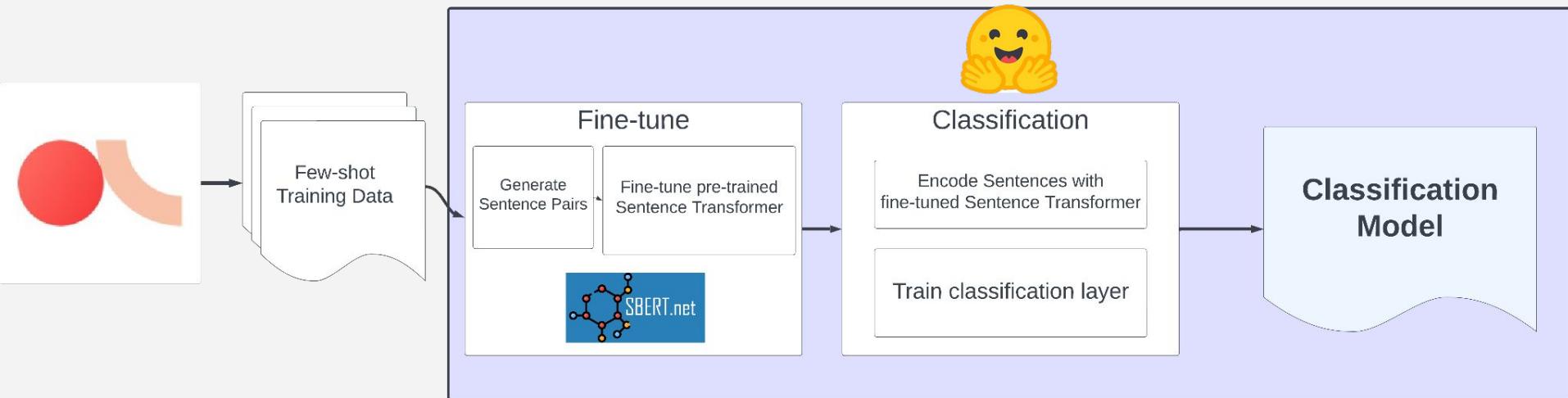


What is SetFit?

- Efficient Few-shot Learning with Sentence Transformers
- [SetFit](#) on HuggingFace
- [GitHub - huggingface/setfit](#)
- Used for multi-class text classification
- [\[arXiv\] Efficient Few-Shot Learning Without Prompts](#)
- Collaboration between HuggingFace and Intel



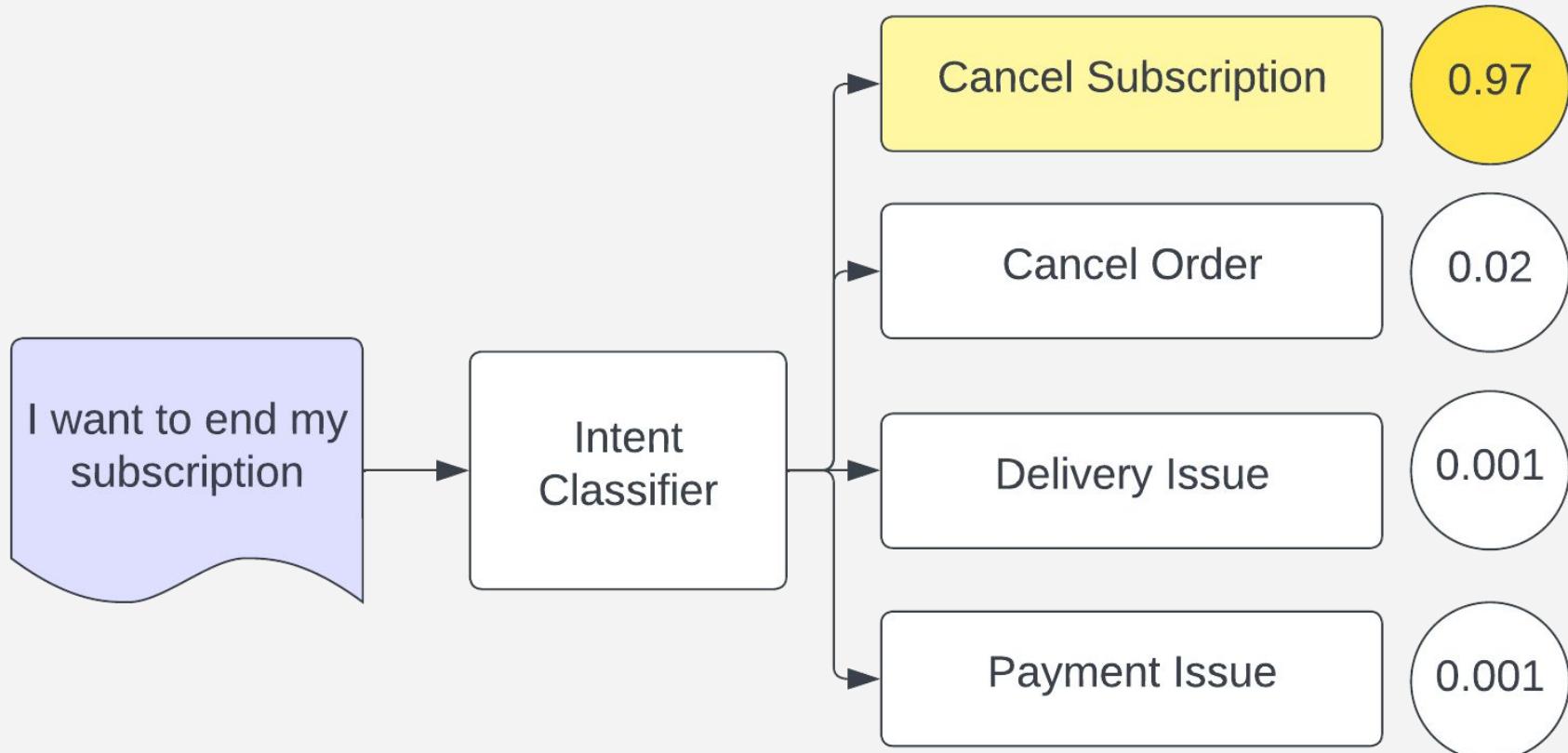
Train Model using SetFit



Why Use SetFit?

- Representation Learning
 - Capture meaningful relationships among items within sets
- Contrastive Objective Function
 - Positive pairs are pulled closer, while negative pairs are pushed apart
- Scalable
- Fast
- SetFit 1.0 was released recently with updated documentation and functionality – thanks to Tom Aarsen!
- No prompting required
- High performance achieved with few examples
- Elegant
- Supported by HuggingFace

Supervised Text Classifier



Batch Inference

- Run on hold-out dataset to examine classifier on the message-level
 - Create classification report
 - Create confusion matrix
- Error Analysis
 - Examine outputs with probabilities in Argilla

If model version passes message-level criteria:

- Run on unseen conversation data to examine classifier on conversation-level

Introduce a query

Predictions

Annotations

Status

Sort

NEW

Help

 Validate

2023-10-17 20:34

Find similar

...

TEXT:

but i cant use thqat account on my computer so I must switch back and forth

Examine outputs with probabilities in Argilla

 Search labels

seller inquiries 0.134%

buyer cancellation r... 0.162%

member manageme... 0.137%

fraudulent seller 0.163%

payment and billing... 0.221%

greeting 0.146%

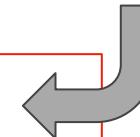
invoice inquiries 0.136%

order quality compl... 0.129%

order how to 0.083%

account inquiries 96.212%

+14

 Discard

Q Introduce a query

Predictions (1) Annotations Status Metadata ⚡ Sort NEW

Predicted as: Select labels

Predicted ok: Select yes/no

TEXT:
Ok. I would like to report an account due to fr

Score: 

Predicted by: 80% to 100%

Cancel

Search labels

seller inquiries 3.132% buyer cancellation ... 0.347% member 0.307%

fraudulent seller 86.521% payment and billin... 0.402% gre 0.358%

invoice inquiries 0.714% order quality compl... 0.307% order how to 0.358% be a seller 0.48%

+14

Segment data by probabilities or any metadata in Argilla

Evaluation

Evaluation Reminder

Coverage: What percent of conversations are assigned an intent

Precision: When an intent is predicted, is it correct?

Frequency: Does the frequency of each contact driver make sense?

Must be evaluated on both the message-level and conversation-level

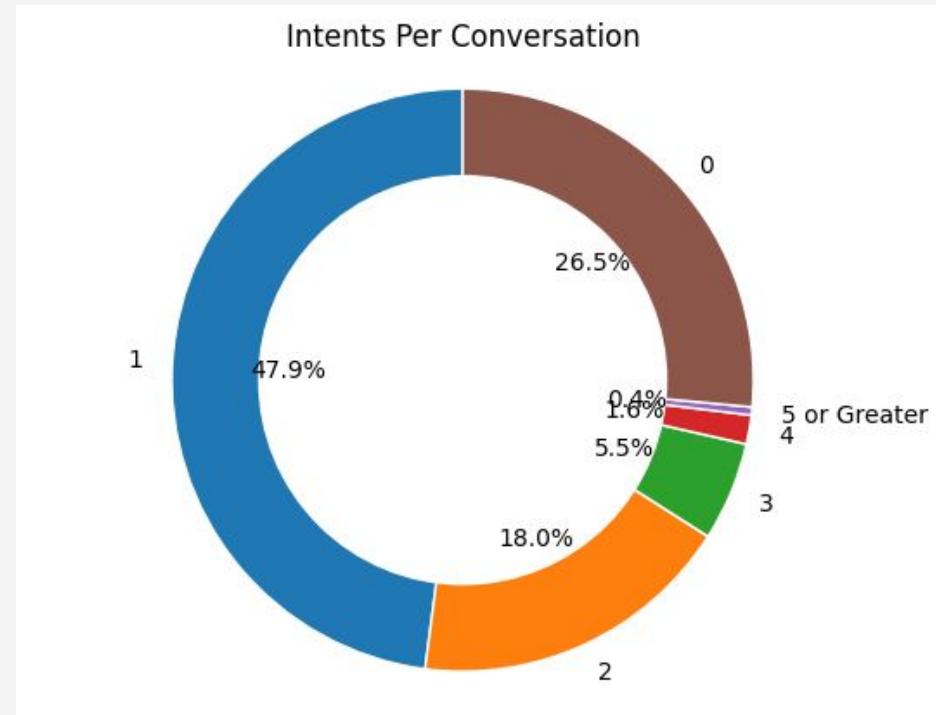
Challenge

How do you evaluate a model on unseen data if you don't have labels?

- Look at aggregate metrics
- Use human annotators
- Use an LLM

Aggregate Metrics

- Coverage
- Intents per Conversation
- Class Frequency



LLM Validator

- A generative system that can be used to validate training data and validate predictions

Prompt Example: “Given {class_name} is defined as {definition}, with the following {examples} classify the following message as YES if it is a {class_name} and NO otherwise:”

- class_name is the accepted class name
- definition is the accepted class definition
- examples are examples for that topic

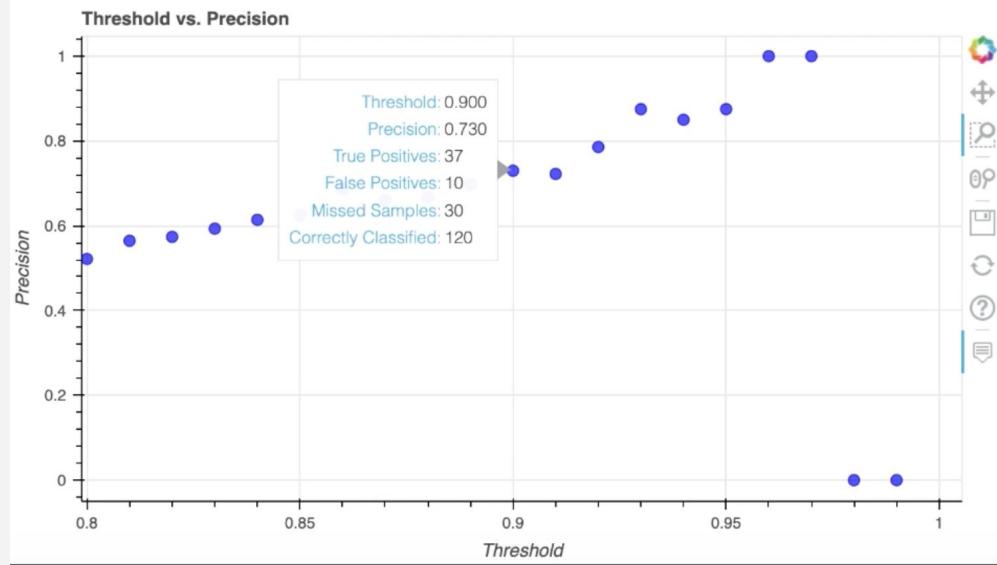
Thresholding

Examining Threshold

- Text - Sample
- Predicted Class
- Predicted Probability
- Label

The Art of Thresholding

- Simply maximizing some metric or function does not work in practice
- All errors are not equal
- Get your hands dirty
- Examine:
 - True Positives
 - False Positives
 - False Negatives
- Set threshold above where errors get flagrant





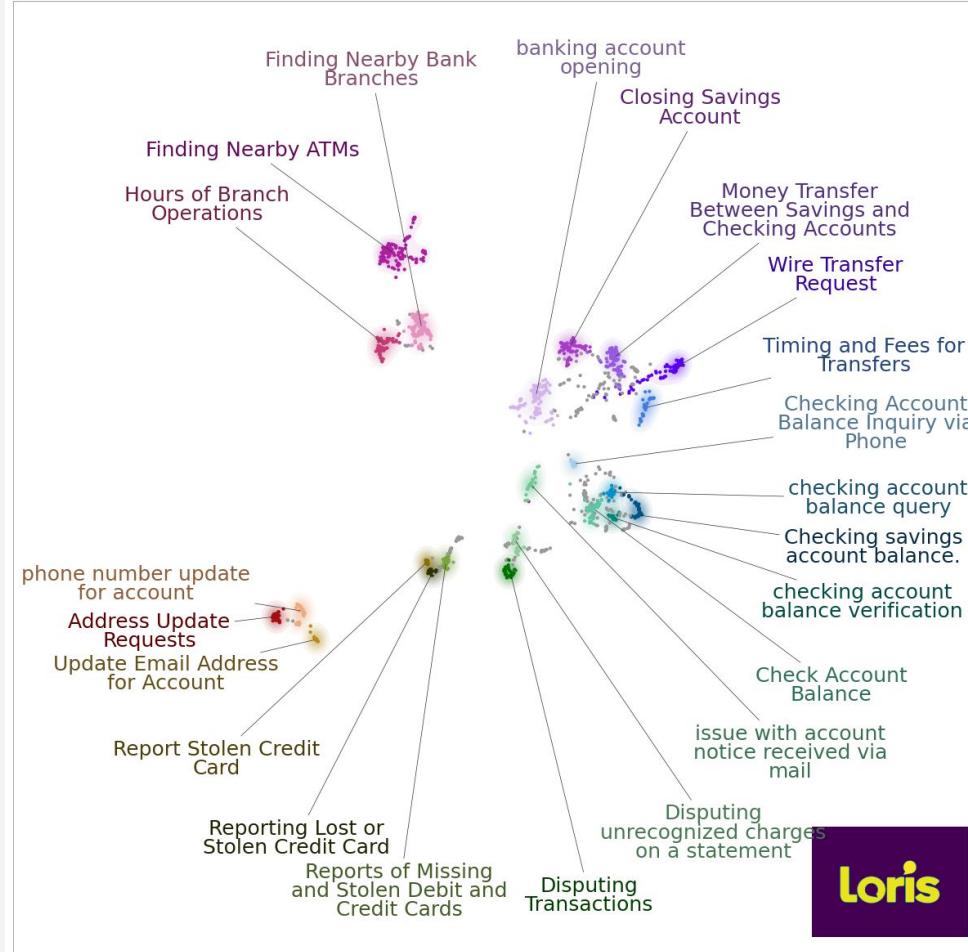
Demo

Demo

- Dataset: [Dialogue State Tracking Challenge from ACL 2023](#)
 - Banking Data
- Explore Data
- Run BERTopic
 - Simulate Intent Discovery
- Train Setfit Model
- Evaluate Classifier
- Visualize what's happening
- Demo Notebooks:
 - [Topic Modeling using BERTopic](#)
 - [SetFit Train Classifier](#)

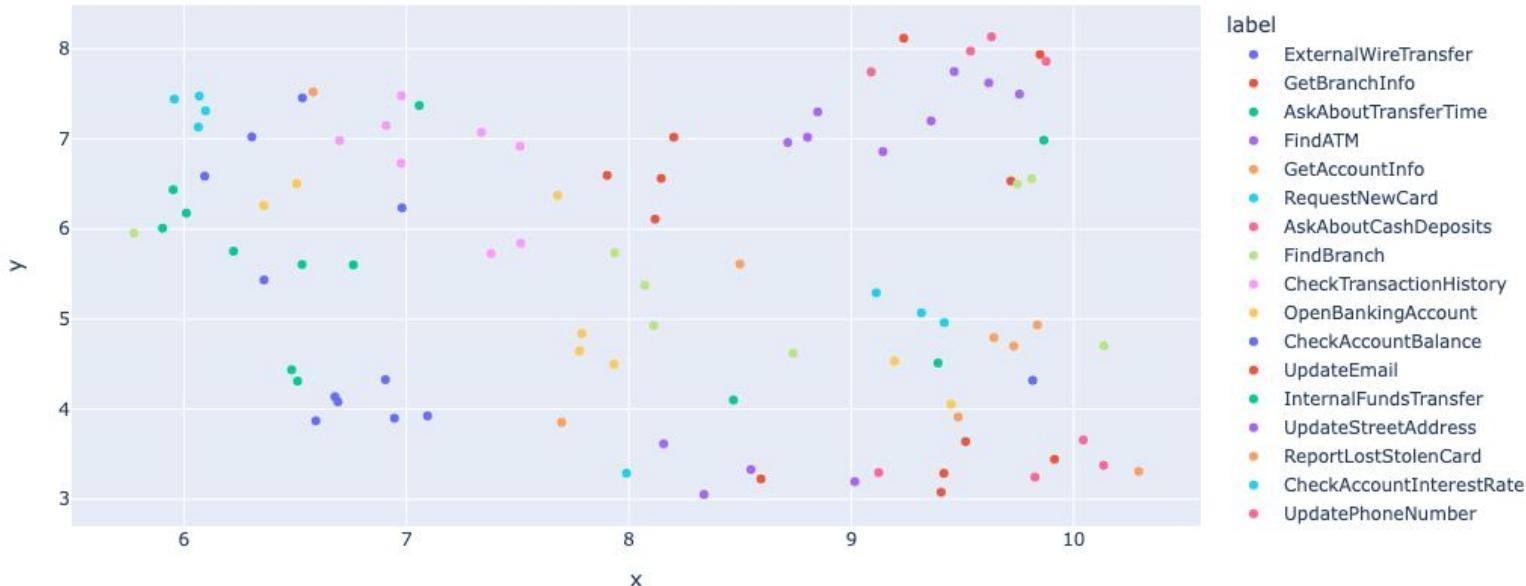
Demo - Loris

Topics labeled with `KeyBERTInspired + OpenAI GPT-3.5`



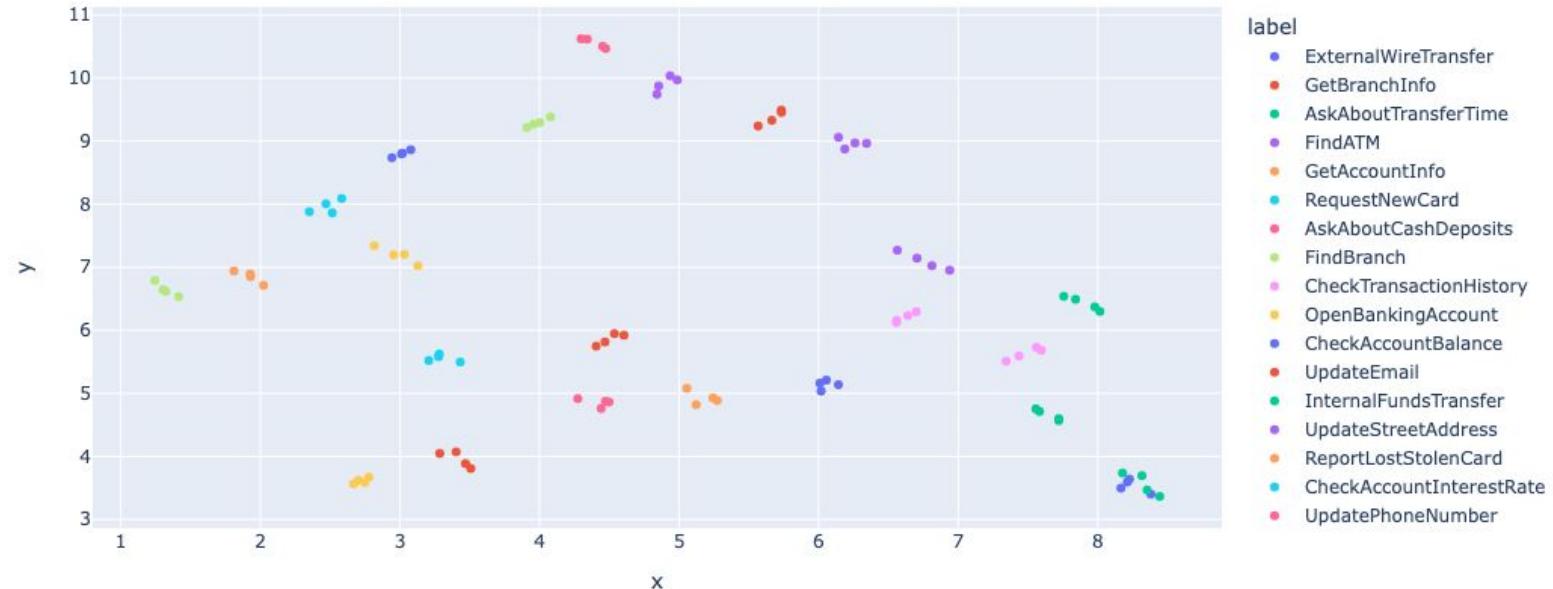
Training Data Before Fine-Tuning

Customer Messages in 2D



Training Data After Fine-Tuning

Customer Messages in 2D

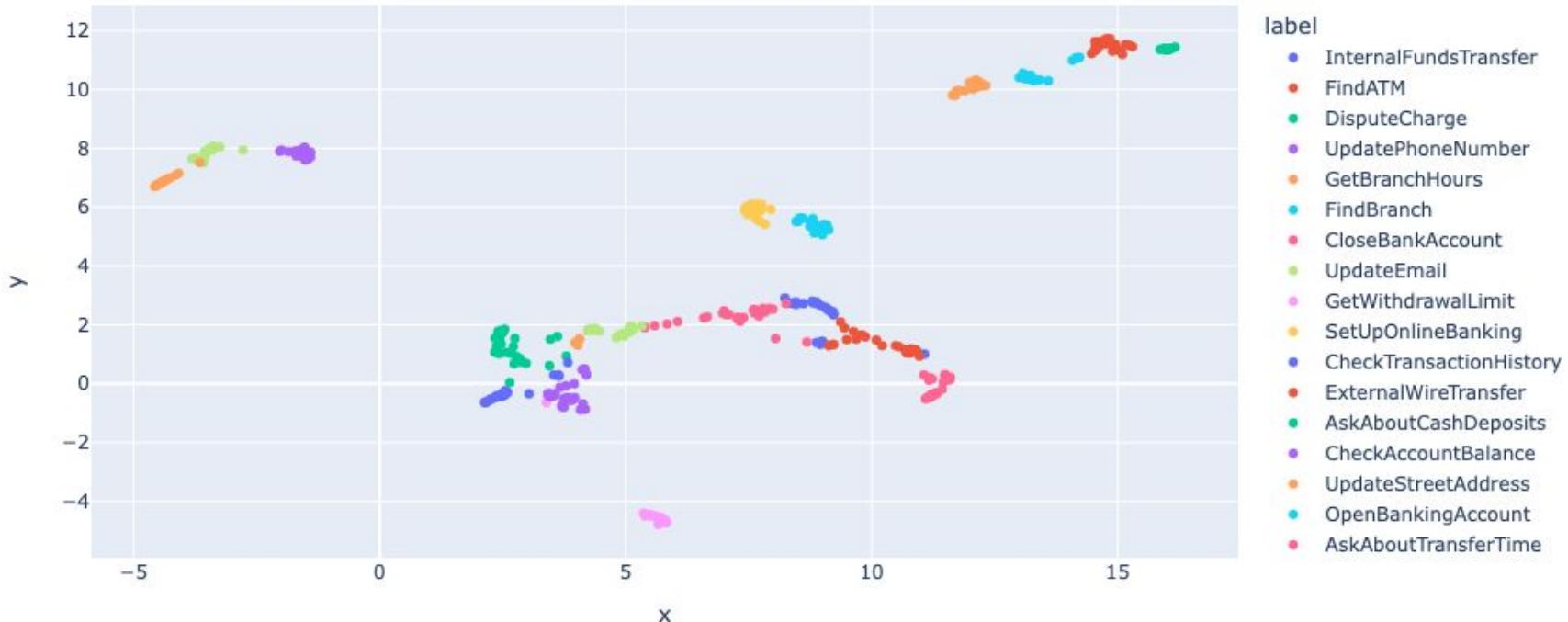


Evaluation

		Confusion Matrix - Banking																			
True label	Predicted label	AskAboutCashDeposits	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
		AskAboutTransferTime	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		CheckAccountBalance	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		CheckTransactionHistory	0	0	1	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
		CloseBankAccount	0	0	0	0	0	29	0	3	0	0	0	0	0	0	0	0	0	0	0
		DisputeCharge	0	0	0	1	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0
		ExternalWireTransfer	0	0	0	0	0	0	0	17	0	1	0	0	6	0	0	0	0	0	0
		FindATM	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0
		FindBranch	0	0	0	0	0	0	0	4	12	0	0	0	0	0	0	0	0	0	0
		GetBranchHours	0	0	0	0	2	0	0	0	0	19	0	0	0	0	0	0	0	0	0
		GetWithdrawalLimit	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0
		InternalFundsTransfer	0	0	0	0	0	0	9	0	0	0	0	17	0	0	0	0	0	0	0
		OpenBankingAccount	0	0	0	0	0	0	0	0	0	0	0	19	0	2	0	0	0	0	0
		ReportLostStolenCard	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	1	0	0	0
		SetUpOnlineBanking	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0
		UpdateEmail	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0
		UpdatePhoneNumber	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	18	0	0	0
		UpdateStreetAddress	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	14	0	0	0

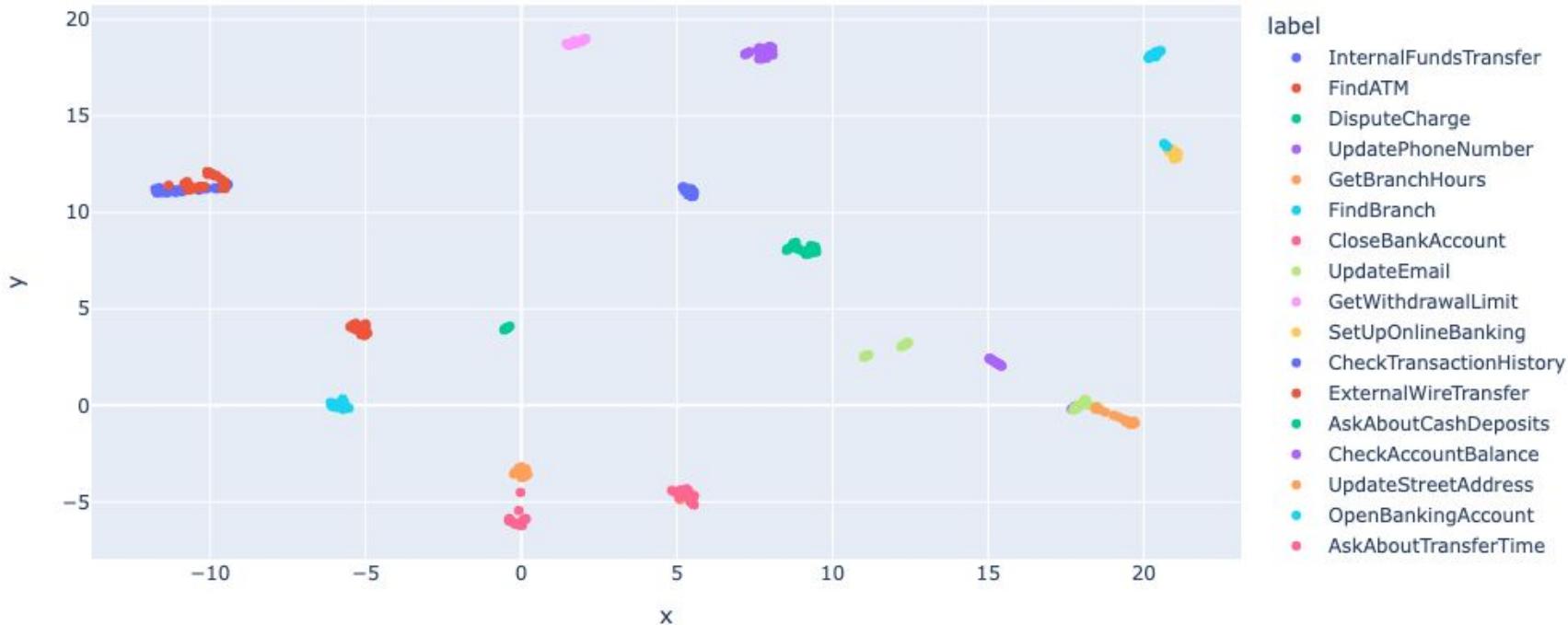
Evaluation Data Before Fine-Tuning

Customer Messages in 2D



Evaluation Data After Fine-Tuning

Customer Messages in 2D

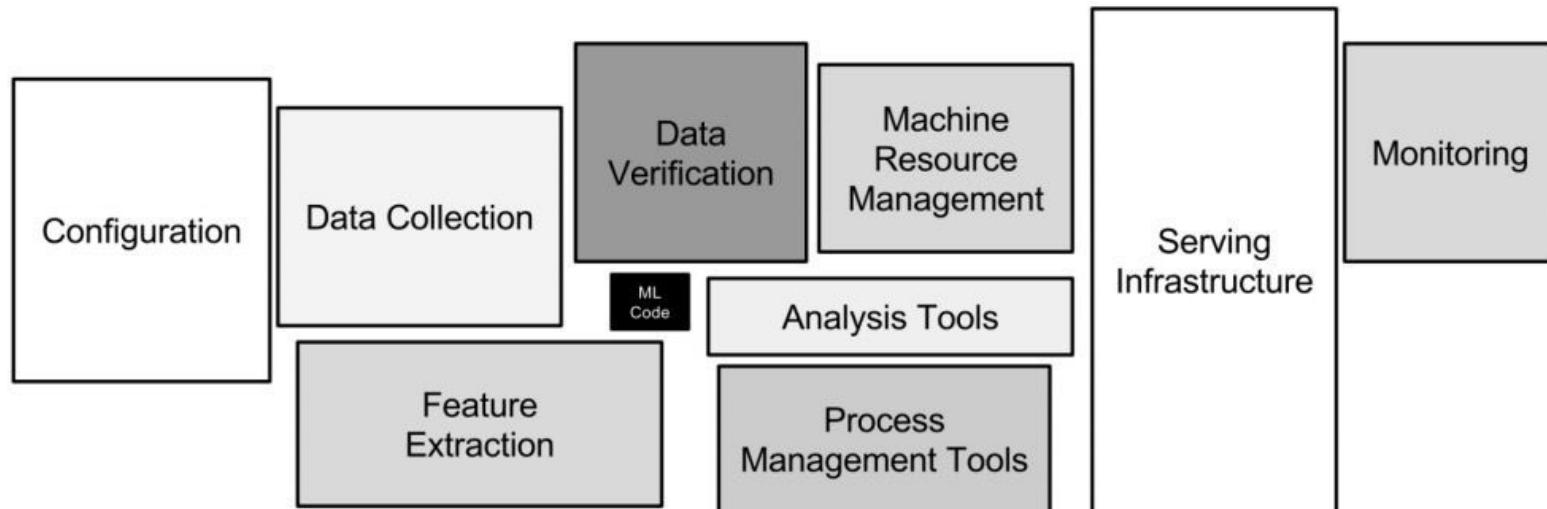


Conclusion

Hidden Technical Debt in Machine Learning Systems

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips

{dsculley, gholt, dg, edavydov, toddphillips}@google.com
Google, Inc.



Learnings

- Understand the problem and use-case deeply
 - Keep revisiting the problem and underlying need
- Use the learnings from other models
 - Create sanity checks - eyeball test sets
- Incorporating classes to ignore improves performance
- Incorporating heuristics can really help
- Training a model is small part
- Creating high quality datasets can help you long term

Learnings

- Segmenting data is a must
- Threshold tuning is almost always needed for multi-class problems
- Creating strong components is important
- You're creating a system not a model
 - Ability to modify is a requirement
- Automation and end to end is a great motivation, but know your data
 - Examine, visualize, explore
 - Include human in the loop when necessary



Takeaways

- Introduction to Loris
- Creating systems to help companies solve problems
 - Challenges in creating client-specific models
 - Example of how to apply NLP to solve problems
- BERTopic is a one-stop shop for topic modeling
- LLMs are great, but they are one potential solution, not the only solution
 - If you're creating a classifier, just create a classifier :)
- Combining multiple approaches often yields the best results

Q & A



Human x Machine = Future of Quality

Loris

Thank You!



[Loris.ai](https://loris.ai)
[Seth Levine | LinkedIn](https://www.linkedin.com/in/sethlevine/)



References

- [Loris.ai](#)
- [Learning from Machine Learning - YouTube](#)
- [BERTopic](#)
- [Argilla docs](#)
- [Sentence-Transformers](#)
- [SetFit](#)
- [DataMapPlot documentation](#)
- [Hidden Technical Debt in Machine Learning Systems](#)
- [It's the Golden Age of Natural Language Processing, So Why Can't Chatbots Solve More Problems?](#)
- [Getting Machine Learning Projects from Idea to Execution](#)

Learning from Machine Learning



Loris CoPilot

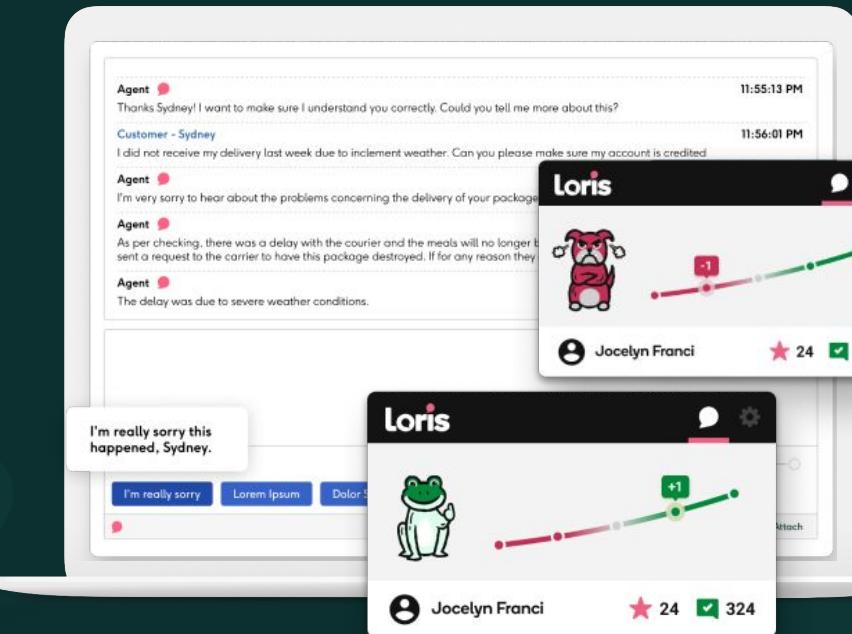
Real-time Agent Assistance

Live agent guidance & feedback

- Uses natural language AI to categorize customer conversations and identify contact drivers
- Provides CSAT score prediction
- Pinpoints both common and emerging areas of friction

Gives leaders

- Single, objective CX benchmarks
- Complete transparency into issues
- Ability to make better use of existing data
- Power to improve CX across multiple functions: product, marketing, customer service, etc.



Loris CQA

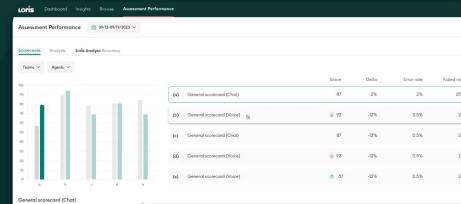
Conversational Quality Assurance

Agent quality & coaching solution

- Analyzes all your customer interactions
- Surfaces most recent & relevant conversations for review
- Automatically scores agent conversation skills
- Provides agent performance & coaching summaries

Helps QA and Agent Managers

- Lower the cost of QA
- Improve agent performance in less time
- Increase consistency & value in QA



This figure displays the Loris Work Assignments interface. It includes a 'Conversation from Last week' section with a message from Brooklyn Simmons on WhatsApp (Chat) at 02:25:24 PM. The message reads: 'Hi, I have a concern about my delivery.' Below this is a 'Calibration' section showing a message from Julie Miles joined chat at 02:23:37 PM. The interface also features a 'Sentiment Graph' showing fluctuating sentiment levels over time, and a 'Why Review?' section with a red 'Threat to post a bad review' button and a green 'Compliment' button. Under 'Intents', there are 'Order late' and 'Delivery speed' buttons. Under 'Tags', there are 'Wrong item delivered' and 'Wrong location' buttons.

This figure shows the Loris Conversation from Today interface. It highlights a conversation between Brooklyn Simmons and Julie Miles. The transcript includes messages such as 'System event - 02:25:24 PM Julie Miles joined chat', 'Hi, I have a concern about my delivery.', 'System event - 02:25:24 PM Brooklyn Simmons joined chat', 'Hi, could you please try to describe the issue in details.', 'It's 7 days late already.', 'Please, help me to understand the matter.', and 'My package was supposed to arrive yesterday, but it hasn't arrived yet, and the tracking information isn't clear.' To the right, a 'Performance assessment' sidebar lists items like 'Effective Communication - 5/5' and 'Did the agent refer to the customer by name within the initial greeting?'. There are also 'Agree', 'Disagree', and 'N/A' buttons for each item. A 'Comment' section provides feedback on the user's question, and a 'Skip conversation' or 'Mark complete' button is at the bottom.

Loris Insights

Customer interaction analytics

CX intelligence platform

- Uses natural language AI to categorize customer conversations and identify contact drivers
- Provides CSAT score prediction
- Pinpoints both common and emerging areas of friction

Gives leaders

- Single, objective CX benchmarks
- Complete transparency into issues
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